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MODELING COMPETITIVE REACTION EFFECTS**

ABSTRACT

In this study I critically review models that specify competitive reaction effects. I discuss different model structures and summarize my findings on competitive reaction effects and factors that explain competitive reactions. I discuss the many models of competitive market response that have been developed and classify them into twelve sets of models that are related to each other in a logical manner through the evolutionary model-building concept.

JEL-Classification: C2, L13, M31.

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1 EVOLUTIONARY MODEL BUILDING

In this study I review models that specify competitive reaction effects. Many of the models that have been developed in the past 40 years are connected to models that were developed earlier. Here, I make the connections between different groups of models by using the evolutionary model-building concept. The basic idea of evolutionary model building is that the model builder begins with a relative simple model. Simplicity is paramount so that managers understand these models. Early applications may reveal shortcomings, and diagnostics can be used to guide further model development. The builder then expands the model, which will lead increasing the complexity of the model (Little (1970); Urban and Karash (1971)).

The evolutionary model-building concept primarily has been applied in the context of *marketing decision models*. By gradually adding more complexities to simpler models, both model builders and model users jointly develop a more complete model by incorporating additional elements. The manager (model user) still understands this more complex

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model, because usually it is her realization that something that was missing led to the increase in complexity.

As an implementation strategy, evolutionary model building increases the likelihood of model acceptance for several reasons¹. First, evolutionary model building implies continuous user involvement, which should lead to reduced resistance to change. Second, it leads to a communication pattern that is more favorable to model acceptance. Finally, the end product makes an optimal match between the environmental complexity of the model and the integrative complexity of the user.

Evolutionary model building can also be observed in the sequence of models and model-building methods that are developed to discover and exploit a particular area in *marketing science*. Models evolve for many reasons. For example, they can be used to identify opportunities to improve an earlier specification; to identify opportunities to apply existing approaches to new problems; to combine different research areas to a new one; to create access to better data; and to make available new methods (specification, estimation and testing, etc.).

In marketing science, the evolutionary model-building steps are performed by several groups, or even generations, of model builders. In an earlier paper, Van Heerde et al. (2002) illustrated the process for models that measure the effectiveness of sales promotions. In this paper I illustrate this process in the context of the models of competitive response. I also give a brief survey of some of the models that have been developed in this area, without having the intention of being complete. In modern marketing, much attention is devoted to competition. The intensity of competition may increase in times when markets show minimal growth. In this study I demonstrate which models can be used to this end. I conclude that there are different niches for different model types, and that these different model types are connected. I use the evolutionary model-building approach to connect the different competitive response models. I begin by discussing the rationale for using competitive response models. In Section 3, I examine the specification and estimation of competitive response models. In doing so, I follow the evolutionary model-building approach. In Section 4, I discuss main findings of research on competition. In Section 5, I consider how companies can use this knowledge to devise their strategies vis-à-vis competition.

2 A RATIONALE TO ACCOUNT FOR COMPETITIVE REACTIONS

Recent research findings (Montgomery et al. (2005)) demonstrate that although managers consider competitors in their decision making, their considerations focus primarily on competitors' past or current behavior rather than on projecting competitors' future reactions. The low incidence of strategic competitor reasoning is due to perceptions of low returns from anticipating competitor reactions more than to the high cost of doing so. Hence, researchers need to convince managers that models and methods can be fruitfully applied to predict competitive reactions and to define firms' future actions.

1 See Leeflang et al. (2000).

Here, I demonstrate how marketing decisions and marketing's contribution to profit are affected if we account for competitive reactions. Thus, I specify the following model:

$$\hat{q} = \hat{\beta}_0 + \hat{\beta}_a \sqrt{a} + \hat{\beta}_{ac} \sqrt{a_c} \quad (1)$$

$$C = c\hat{q} + FC \quad (2)$$

$$\hat{\pi} = p\hat{q} - C. \quad (3)$$

In Equations (1)-(3), \hat{q} is the estimated demand of a brand (say brand j) in units, a , a_c is the advertising expenditures of brand j and the advertising expenditures of a competitor respectively, C is the total cost, c is the variable cost per unit, FC is the fixed cost, and π is the profit. I do not use indexes j (brand) and t (time) just for the sake of restricting the number of indices. I assume that the model builder estimates parameters $\hat{\beta}_a$ and $\hat{\beta}_{ac}$ by using time series data. $\hat{\beta}_{ac}$ represents the effects of competitive actions. Throughout, I assume that $\hat{\beta}_a > 0$, $\hat{\beta}_{ac} < 0$ and $p > c$. The reduced form of Equations (1)-(3) is:

$$\hat{\pi} = (p - c)(\hat{\beta}_0 + \hat{\beta}_a \sqrt{a} + \hat{\beta}_{ac} \sqrt{a_c}) - a - FC. \quad (4)$$

I obtain the optimal advertising budget by differentiating (4) with respect to a and equating this expression to zero. First, I assume that there is no relation between a and a_c . Hence, I get²:

$$a_{opt} = \frac{\{(p - c)\hat{\beta}_a\}^2}{4}. \quad (5)$$

The higher the margin, $(p - c)$, and the effectiveness of advertising, $\hat{\beta}_a$, the higher the optimal advertising budget will be.

I now assume that the competitor reacts with a_c on a :

$$\hat{a}_c = \hat{\alpha}_0 + \hat{\alpha}_1 a \quad (6)$$

where I assume that $\hat{\alpha}_1 > 0$.

The effect of a change in a on q is now represented by:

$$\frac{\partial q}{\partial a} = \frac{\partial q_j}{\partial a} + \frac{\partial q_j}{\partial a_c} \cdot \frac{\partial a_c}{\partial a} \quad (7)$$

where $\frac{\partial q_j}{\partial a}$ is the *direct* effect of advertising on demand and $\frac{\partial q}{\partial a}$ is the *total* effect of advertising on demand. Given Equations (1) and (6), I have

- 2 To make sure that this expression for a_{opt} corresponds to a maximum, I examine the second-order conditions. I find that, given the assumptions about $\hat{\beta}_a$, $\hat{\beta}_{ac}$ and $(p - c)$, I can expect the second-order condition to be negative, which leads to a maximum value of π .

$$\frac{\partial q}{\partial a} = \frac{1}{2} \cdot \hat{\beta}_a \cdot a^{-1/2} + \hat{\alpha}_1 \cdot \frac{1}{2} \hat{\beta}_{ac} \cdot a_c^{-1/2}. \quad (8)$$

Given that $\hat{\beta}_{ac} > 0$, the effect of brand j 's advertising on brand j 's demand is lower than if there is no competitive reaction. This also means that the marginal revenue product of advertising $p \cdot \frac{\partial q}{\partial a}$ is lower, which has implications for the optimal advertising expenditures and the optimal profit. The optimal advertising expenditures, and thus the optimal profit, are a function of $\hat{\beta}_{ac}$, $\hat{\alpha}_1$ and a_c :

$$a_{opt} = \frac{\{(p - c)\hat{\beta}_a\}^2 a_c}{\{2\sqrt{a_c} - \hat{\beta}_{ac}\hat{\alpha}_1(p - c)\}^2}. \quad (9)$$

If managers do not account for competitive actions and instead determine their budget on Equation (5), they will spend too much on advertising. This statement is conditional on the assumption that the estimates are unbiased. Biases in parameter estimates also lead to non-optimal decisions. Hence, managers' decision-making will benefit from anticipating competitors' reactions and estimating the values of $\hat{\beta}_{ac}$ and $\hat{\alpha}_1$, and then forecasting a_c . There are different opportunities to obtain these forecasts, ranging from naïve methods such as $a_{ct} = a_{c,t-1}$ or $a_{ct} = 1.05a_{c,t-1}$ (competitive advertising increases with 5% over time) to methods that use competitive reaction functions. For a more in-depth review see, for example, Alsem and Leeftang (1994), and Alsem et al. (1989).

3 MODELING COMPETITIVE RESPONSIVENESS: SPECIFICATION AND ESTIMATION

In this section I briefly sketch some opportunities for modeling competitive behavior. Many models and methods attempt to diagnose and predict competitive behavior. In *Figure 1*, I depict the modeling of competitive responsiveness functions as an evolutionary process. The figure shows the different steps involved and twelve sets of models.

The first step consists of building relatively simple models³, which may subsequently be expanded to incorporate additional elements, thus becoming more complex. Day and Wensley (1988) dichotomize competitive response models into competitor-centered methods and customer-focused approaches. *Competitor-centered assessments* use direct management comparisons between the firm and a few target competitors. These models often include a determination of the relative strengths and weaknesses of each firm and the extent to which competitors quickly match marketing activities initiated by another firm.

Customer-focused assessments start with detailed analyses of customer benefits within end-user segments. These models work backward from the customer to the company to identify the necessary actions that will improve performance. Customer-focused assessments become possible by calibrating *demand models* that include competitive marketing variables. Classical micro-economic theory (see 1 in *Figure 1*) considers the impact of competitive actions on demand on the basis of cross-elasticities. However, more specific marketing

3 Cf. Urban and Karash (1971); Van Heerde et al. (2002).

models also include marketing-mix instruments other than price, and use brand sales as the demand measure.

In addition, demand equations may be supplemented by competitive reaction functions (Telser (1962)). For example, Lambin, Naert, and Bultez (1975) calibrate competitive reaction functions (see 2 in *Figure 1*) using data about a low-priced consumer durable good in West Germany. Extensions to their classical "LNB model" include more *advanced competitive reaction functions* (3) and *demand functions* (4). Using a framework based on cross-tabulations, other researchers have also studied reaction functions and demand functions simultaneously (5). Furthermore, VARX models (Vector Autoregressive models with exogenous variables) provide a way to estimate advanced demand and competitive reaction functions simultaneously (6).

Managers can use these models (1-6) to determine the optimal marketing mix for one brand, assuming particular reaction patterns by competitors. That is, they do not offer a simultaneous optimum for all brands in a product class. *Game-theoretic approaches* address this issue, although most early game-theoretic models were theoretical and had no empirical applications⁴ (see 7 in *Figure 1*). Since the early 1980s, there have been major advances in game theory, particularly in the area of dynamic games. As a result, the theory has become far more applicable to the modeling of real-world competitive strategies. Even more recently, marketers have embraced the new empirical industrial organization (NEIO)-based approach to infer the competitive behavior of firms⁵ in terms of both horizontal (8) or vertical (9) competition, or both. Horizontal competition occurs between brands or organizations (retailers) that compete to match the preferences of the customers; vertical competition exists within the same (distribution) channel between different partners that have, at least in principle, different groups of customers. Therefore, vertical competition deals with the allocation of the total profits in the distribution channel that flows from manufacturers to wholesalers to retailers. In the structural models such as these, price levels in the market depend on demand and cost conditions, as well as the nature of interfirm interactions in the market. By estimating both demand and supply functions, this approach decomposes price levels into the unique effects of demand, cost, and competitive behavior. (I note that these models typically assume steady-state competitive behavior.) In models that study time-varying competition (10), the direct effects of demand and cost changes on prices and the indirect effects on *competitive intensity* all come into play⁶. One of the most advanced models used to study competitive response (11)⁷ considers both vertical and horizontal competition; is based on advanced demand and competitive reaction functions, and is dynamic. Finally, new models of competitive response (12) should satisfy various criteria and deal with many different issues such as endogeneity (Shugan (2004); (2005)) and market evolution (Soberman and Gatignon (2005)).

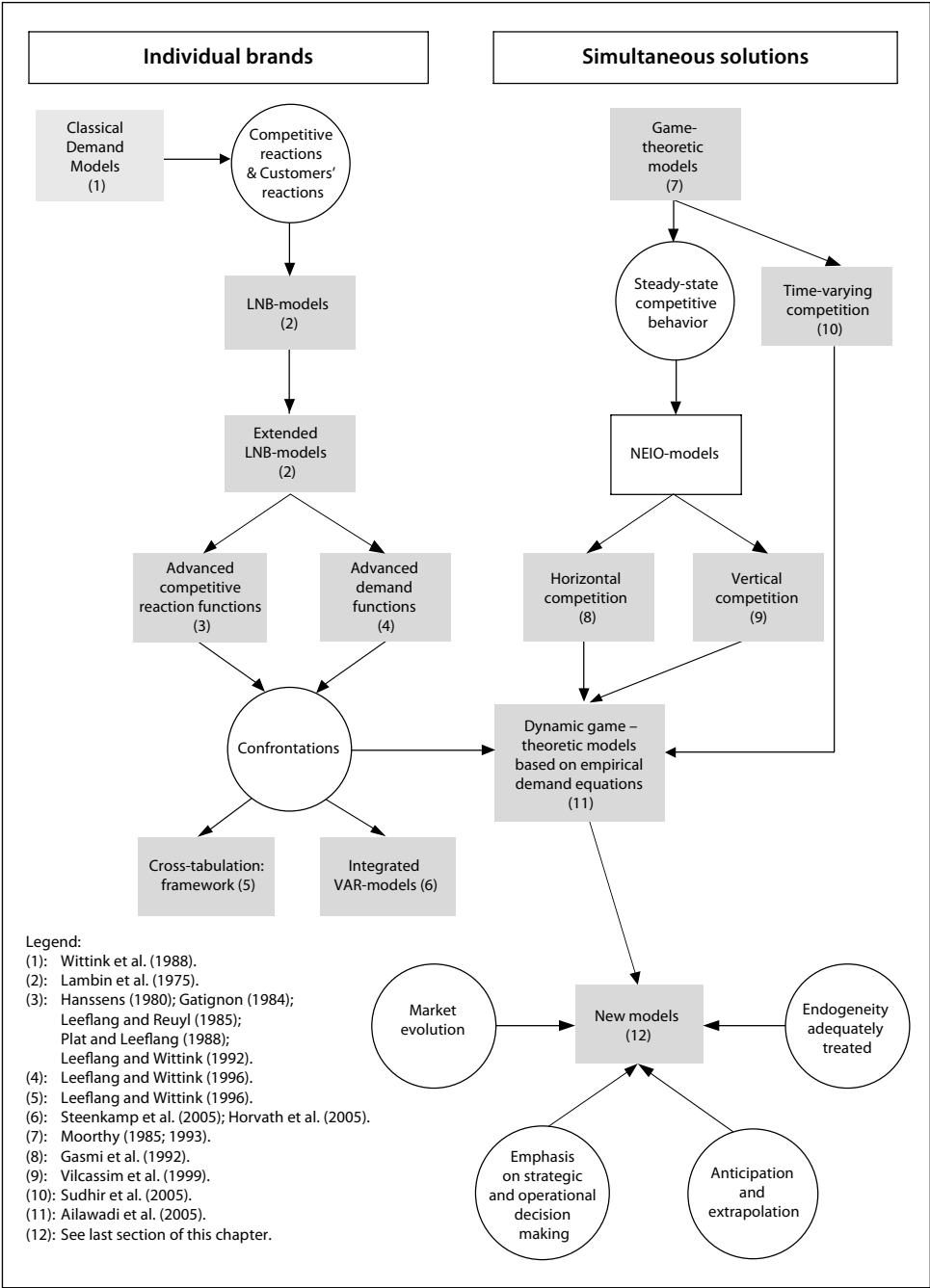
4 Examples are Friedman (1958); Mills (1961); Shakun (1966); Baligh and Richartz (1967); Gupta and Krishnan (1967a; b); Krishnan and Gupta (1967).

5 See Kadiyali et al. (2001) for a review.

6 Examples are models developed by Ellison (1994) and Sudhir et al. (2005).

7 The model of Ailawadi et al. (2005) has these features.

Figure 1: Evolutionary model building in competitive responsiveness



3.1 CLASSICAL DEMAND MODELS

Incorporating competitive marketing instruments into a demand model offers opportunities to determine the effects of competitive actions in a relatively simple way. As an example, I specify the following model:

$$\hat{q} = \hat{a} + \hat{\beta}_p p + \hat{\beta}_{pc} p_c + \hat{\beta}_a a + \hat{\beta}_{ac} a_c \quad (10)$$

where \hat{q} is the estimated demand of a brand (say brand j) in units, a , a_c is the advertising expenditures of brand j and the advertising expenditures of a competitor and p , p_c are the price of the brand j and the competitive price, respectively. $\hat{\beta}_{pc}$ and $\hat{\beta}_{ac}$ represent the effects of competitive actions on \hat{q} . The effects of competitive actions on sales can be predicted by substituting the expected future values of p_c and a_c in the estimated relation⁸. This classical model does not account for how brand j may react to competitive actions or how brand j 's competitor reacts in turn to brand j 's actions, nor does it address how these reactions ultimately modify consumer demand. One of the first studies to explicitly model these competitive reaction effects is Kotler (1965). Kotler's model has been modified in the so-called LNB model.

3.2 LNB MODELS

I consider the following functions for Q , product class sales, and m , a brand's market share:

$$Q = Q_T(p, a, k, p_c, a_c, k_c, ev) \text{ and } m = m_j(p, a, k, p_c, a_c, k_c) \quad (11)$$

where Q_T , m_j are the functional forms for Total Quantity and brand j 's market share, respectively; p , p_c is the price of a brand (say, brand j) and an index of competitors' prices, respectively; k , k_c is a quality measure for brand (j) and an index of competitors' quality measures, respectively; a , a_c is the advertising expenditure of brand (j) and an index of competitors' advertising expenditures, respectively; and ev is a vector of environmental variables. These functions also provide examples of equations that represent consumers' reactions to competitive actions (p_c , a_c , k_c). Brand j 's sales elasticity with respect to its advertising ($\eta_{q,a}$) equals the total product class elasticity ($\eta_{Q,a}$) plus the total market share elasticity with respect to brand j 's advertising ($\eta_{m,a}$):

$$\eta_{q,a} = \eta_{Q,a} + \eta_{m,a}. \quad (12)$$

These elasticity measures capture the effect of one brand's advertising on consumer demand, but to capture total actual impact, I must consider how competitors react to brand advertising changes and how this reaction modifies consumer demand. The competitive reactions belong to the set of competitor-centered approaches. I distinguish *direct*

⁸ See, for example, Alsem et al. (1989).

and *indirect partial effects* of brand j 's advertising on product class sales and on brand j 's own market share. An indirect partial effect captures the following scenario: If brand j changes its advertising expenditure level (Δa), then competitors may react by similarly, adapting their spending level (Δa_c), and, as discussed in Section 2, a_c in turn influences Q and/or m . According to this explanation, which is the usual assumption in oligopoly theory, competitors react with the same marketing instrument as that which caused their reactions. Thus, competitors react to a change in price for j by changing their prices, to a change in advertising by an advertising response, and so forth. This type of reaction reflects the simple competitive reactions case. A more realistic approach, consistent with the concept of the marketing mix, accommodates multiple competitive reactions such that a competitor may react to a price change not just by changing its price, but also by changing its advertising and other such marketing instruments.

With a general case of multiple competitive reactions, I can write $\delta Q/\delta a$ and $\delta m/\delta a$ as follows:

$$\frac{\delta Q}{\delta a} = \frac{\delta Q_T}{\delta a} + \frac{\delta Q_T}{\delta p_c} \frac{\delta p_c}{\delta a} + \frac{\delta Q_T}{\delta a_c} \frac{\delta a_c}{\delta a} + \frac{\delta Q_T}{\delta k_c} \frac{\delta k_c}{\delta a} \quad (13)$$

and

$$\frac{\delta m}{\delta a} = \frac{\delta m_j}{\delta a} + \frac{\delta m_j}{\delta p_c} \frac{\delta p_c}{\delta a} + \frac{\delta m_j}{\delta a_c} \frac{\delta a_c}{\delta a} + \frac{\delta m_j}{\delta k_c} \frac{\delta k_c}{\delta a}. \quad (14)$$

In (13) and (14) $\delta Q_T/\delta a$, $\delta m_j/\delta a$ are the *direct* effects and $\delta Q/\delta a$, $\delta m/\delta a$ are the *total* effects.

By multiplying both sides of equation (13) by a/Q , I obtain the product-class elasticity, $\eta_{Q,a}$:

$$\eta_{Q,a} = \eta_{Q_T,a} + (\rho_{p_c,a})(\eta_{Q_T,p_c}) + (\rho_{a_c,a})(\eta_{Q_T,a_c}) + (\rho_{k_c,a})(\eta_{Q_T,k_c}) \quad (15)$$

where $\eta_{Q_T,a}$ is the direct product-class sales elasticity with respect to brand j 's advertising; η_{Q_T,u_c} is the product-class sales elasticity with respect to competitors' marketing instrument u_c ($= p_c, a_c, \text{ or } k_c$); and $\rho_{c,a}$ is the reaction elasticity of competitors' instrument u_c ($= p_c, a_c, \text{ or } k_c$) with respect to brand j 's advertising expenditures.

Similarly, I can decompose $\eta_{m,a}$ as follows:

$$\eta_{m,a} = \eta_{m_j,a} + (\rho_{p_c,a})(\eta_{m_j,p_c}) + (\rho_{a_c,a})(\eta_{m_j,a_c}) + (\rho_{k_c,a})(\eta_{m_j,k_c}). \quad (16)$$

The LNB model can be fruitfully applied if a company is not particularly interested in the effects of individual competitors, but rather in the effects of the aggregate of other brands/firms; does not face vertical competition; and specifies its marketing mix independently from retailers. Extended LNB models relax one or more of these conditions. Hence, the extended LNB models are the result of identifying opportunities to improve

an earlier specification. They constitute the next generation of models of competitive market response.

3.3 EXTENDED LNB MODELS WITH ADVANCED COMPETITIVE REACTION FUNCTIONS

The extended LNB models relax the assumptions that all brands are represented by an aggregate brand, and that marketing mix decisions are specified independently from retailers.

The LNB model assumes that the market comprises a leader that uses marketing instruments p , a , and k , and a follower, defined as the aggregate of other firms in the market. For example,

$$p_c = \sum_{r=2}^n \frac{p_r}{(n-1)}, p = p_1, a_c = \sum_{r=2}^n a_r, a = a_1, \quad (17)$$

and so forth, where n = total number of brands and “1” indicates the leading brand.

In extended LNB models, modelers make no distinction between leaders and followers. Instead, they consider all brands separately in what amounts to a decomposition of competitive interactions.

An example of an extended LNB model is Hanssens's (1980) approach⁹:

$$x_{\ell jt} = h(x_{\ell' rt} - x_{\ell jt}); \ell, \ell' = 1, \dots, L; j, r = 1, \dots, n, j \neq r; t = 1, \dots, T \quad (18)$$

where $x_{\ell jt}$ is the value of the ℓ -th marketing instrument of brand j in period t .

Equation (18) allows for joint decision-making when $j = r$, which summarizes the possibility that changes in one variable result in changes in one or more other variables for a given brand. These relations between different variables for the same brand are known as *intrafirm* activities.

In equation (18) the number of equations to be estimated is Ln , and the many predictor variables can make its estimation difficult. For example, each equation may have $(Ln - 1)$ predictors, even if I do not consider time lags. Hence, if I consider five ($L = 5$) marketing instruments of five brands ($n = 5$), I have 24 predictors. This implies that I need about $(5 \times 24) \approx 120$ observations to obtain reliable estimates. Given that the time horizon used for calibration should not be too long (say, two years), I must work with weekly data. The data that researchers use to calibrate the reaction functions in these studies generally involve manufacturers' actions and reactions. In the past, researchers used monthly, bimonthly, or quarterly data, but scanner data offers many new opportunities to study competitive reactions. However, calibrating competitive reaction functions with weekly scanner data collected at the

9 In (18) the “subtraction” of $x_{\ell jt}$ means that instrument ℓ for brand j in period t is *not* a predictor variable.

retail level involves its own problems, because changes in marketing activities may reflect the actions and reactions of both retailers and manufacturers. For example, ultimately, price decisions about a brand are made by the retailers (Kim and Staelin (1999)). Temporary price cuts, displays, refunds, and bonuses introduced at the retail level depend on the degree to which retailers accept (pass-through rates) promotional programs. Thus, especially with scanner data, researchers who estimate competitive reaction functions should create models that reflect the roles of both the manufacturers and the retailers.

Another issue is the interpretation of the signs in the competitive reaction functions. For example, the question is whether a negative sign is a reaction, or just an association between two variables. The answer touches on causality issues. Leeflang and Wittink (1992) develop models that explicitly account for these roles. I do not discuss how these roles are reflected in their models, but concentrate on their basic model. Using weekly scanner data that refer to 76 weeks and seven brands, the authors consider the following marketing instruments: price (p), sampling (free products and gifts) (sa), refunds (giving money back on, for example, a bank account) (rf), bonus offers (more content of a product at the same price) (bo), and featuring (retailer advertising) (ft). For each brand, the authors estimate competitive reaction functions for each marketing instrument and express the criterion variables in the competitive reaction function as changes. For example, the logarithm of the ratio of prices in two successive periods represents price, because price changes for brands with different regular price levels are more comparable on a percentage basis rather than on an absolute basis. In this way the authors also circumvent price inflation issues.

Leeflang and Wittink (1992) specify other promotional activities in terms of simple differences, because zero values may occur in these cases. Such values imply that logarithms cannot be used. To illustrate the price of brand j (p_{jt}), the authors specify the following competitive reaction function:

$$\ln\left(\frac{p_{jt}}{p_{j,t-1}}\right) = \alpha_j + \sum_{r=1, r \neq j}^n \sum_{t^*=1}^{T^*+1} \beta_{jrt^*} \ln\left(\frac{p_{r,t-t^*+1}}{p_{r,t-t^*}}\right) + \sum_{t^*=2}^{T^*+1} \beta_{jjt^*} \ln\left(\frac{p_{j,t-t^*+1}}{p_{j,t-t^*}}\right) \quad (19)$$

$$+ \sum_{r=1}^n \sum_{t^*=1}^{T^*+1} \sum_{x=1}^4 \tau_{xjrt^*} (x_{r,t-t^*+1} - x_{r,t-t^*}) + \varepsilon_{jt}$$

for $j = 1, \dots, n$ and $t = T^* + 2, \dots, T$;

where $x = 1 = sa$; $x = 2 = rf$; $x = 3 = bo$; $x = 4 = ft$; T^* is the maximum number of time lags ($T^* = 10$); T is the number of observations available; n is the number of brands; and ε_{jt} is a disturbance term.

Equation (19) also includes lagged endogenous variables. These variables account for the phenomenon that periods with heavy promotions are frequently followed by periods with relatively low promotional efforts. Equation (19) makes it clear that the number

of predictor variables is so large that they easily exceed the number of observations. For example, suppose that $n = 7$ (brands), each with five instruments, $T^* = 10$ (lagged periods), and $T = 76$. Thus one would have 76 observations to estimate 391 parameters, under the assumption that all manufacturers use all marketing instruments. Therefore, in their model, Leeflang and Wittink (1992) use bivariate causality tests to select potentially relevant predictor variables (see also, Bult et al. (1997))¹⁰.

3.4 EXTENDED LNB MODELS WITH ADVANCED DEMAND FUNCTIONS

In these models, researchers relax the assumptions that a limited number of marketing instruments of one competitive brand affects the demand function. This relaxation also leads to improved specifications. A customer-focused approach relies on information about consumers' sensitivity to changes in marketing instruments; that is, it considers estimated market response functions. I discuss an example in which demand is specified at the market-share level. I assume competitive behavior is asymmetric. The structure of the model example (developed by Leeflang and Wittink (1996)) is similar to that used for the competitive reactions (Equation (19)). The criterion variable is the natural logarithm of the ratio of market shares in successive periods for brand $j = 1, \dots, n$: $\ln(m_{jt}/m_{j,t-1})$, which in turn is a function of the natural logarithm of the ratio of prices in successive periods and the first differences of the four promotional variables introduced before of all brands $r = 1, \dots, n$:

$$\begin{aligned} \ln\left(\frac{m_{jt}}{m_{j,t-1}}\right) = & \lambda_j + \sum_{r=1}^n \sum_{t^*=1}^{T^*+1} \gamma_{jrt^*} \ln\left(\frac{p_{r,t-t^*+1}}{p_{r,t-t^*}}\right) \\ & + \sum_{r=1}^n \sum_{t^*=1}^{T^*+1} \sum_{x=1}^4 \xi_{xjrt^*} (x_{r,t-t^*+1} - x_{r,t-t^*}) + u_{jt} \end{aligned} \quad (20)$$

where u_{jt} is a disturbance term, p represent prices and the x 's are the non-price promotional variables. Leeflang and Wittink confront these demand equations with the more advanced competitive reaction functions (19). Leeflang and Wittink (1996) have also calibrated this model, using weekly data that covers 76 weeks.

3.5 FRAMEWORK AND CROSS TABULATIONS

The framework approach can enhance the congruence between competitor-oriented and customer-focused decision-making, because the framework itself relates consumer response and competitive reaction effects and thus provides a basis for categorizing over- and under-reactions by managers. Hence, this approach combines advanced

10 For a discussion of other models that calibrate competitive reaction functions, see Kadiyali et al. (1999); Vilcasim et al. (1999). In all cases, the reaction functions attempt to capture the use of marketing instruments to react to changes in other instruments without regard to consumer responses.

competitive reaction functions with advanced demand functions. The combination of different models leads to the next step in the evolutionary model-building process. In the framework approach which is used by Leeflang and Wittink (1996) there are three kinds of elasticities: reaction elasticity, cross-elasticity, and own elasticity. For simplification, the framework is restricted to the absence or presence of effects, such that the elasticities are either zero or not, which results in eight possible combinations (see *Table 1*). Leeflang and Wittink (1996) consider two brands: the defender brand *i* and the attacker brand *j*. Brand *i* uses marketing instrument *ℓ* to react to an attack of brand *j*.

Table 1: A framework of cross-market share-, competitive reaction, and own-market share effects

Cross-Brand Market Share Effect				
Own-Brand Market Share Effect	YES		NO	
	Competitive Reaction Effect		Competitive Reaction Effect	
	YES	NO	YES	NO
YES	A Intense competition	C Underreaction; Lost opportunity for defender ^a	E Defender's game	G No competition
	B Spoiled arms for defender ^a	D Ineffective arms	F Overreaction; Spoiled arms for defender ^a	H No competition
NO				

^a Note that the defender brand may lack information about its own-brand market share effects.
Source: Leeflang and Wittink (1996, 106)

In cell A of *Table 1* all three effects are non-zero, which implies intense competition. Thus, brand *i* uses marketing instrument *ℓ* to restore its market share, influenced by brand *j*'s use of variable *h*. In the presence of a cross-brand market-share effect, brand *j* cannot recover its loss of market share if the own-brand market share effect is zero, as in cell B; there is no competitive reaction effect, as in cell C; or there is neither a competitive reaction effect nor an own-brand market share effect, as in cell D. In *Table 1*, Cell B indicates the use of an ineffective instrument ("spoiled arms") chosen by *i* to react to *j*. Cell C represents *under-reactions*, such that brand *i* should defend its market share but does not react, even though instrument *ℓ* is effective. Leeflang and Wittink (1996) define this case as a lost opportunity for defender *i*. If there are no reaction effects and the own-brand market share elasticities equal zero, Leeflang and Wittink (1996) recognize ineffective arms (cell D).

If there is no cross-brand market share effect, then competitive reaction effects should not occur if the firm's objective is simply to preserve its market share. In the third column in *Table 1*, cells E through F identify some associated *overreactions*. In cell E (defender's game), the reactions include an instrument that has an own-brand effect, even though no cross-brand market share effect exists. Cell F involves (unnecessary) reactions with an ineffective instrument. Cells G and H reflect no competition because of the absence of both a cross-brand market-share effect and a competitive reaction effect.

This framework suggests that knowledge about *cross-* and *own-brand* market-share effects enables managers to better prepare themselves for competitors' activities in terms of whether and which reactions are desirable. Thus, a consumer-focused approach that captures consumer responses to marketing helps management diagnose competition. Although the estimation of reaction matrixes captures the nature of competitive reactions, it falls short of explaining reaction patterns. In other words, it fails to provide sufficient insight into the underlying reasons for the observed reactions (Ramaswamy et al. (1994); Kadiyali et al. (2001)). Another drawback of competitive reaction models involves understanding who is the defender and who is the attacker, i.e., the one that initiates a move. In response, researchers developed the VARX and the NEIO models to provide such insights. The availability of more data (scanner data at the store level) and new methods (VARX modeling) determine this step in the evolutionary model-building process.

3.6 VARX MODELS

Modern time-series analysis (TSA) offers the opportunity to use demand functions and reaction functions *simultaneously* to diagnose and predict competition. VARX models can be used in cases in which the marketer wants to account for the dynamic effects of marketing instruments on the sales of individual brands in a market and when, or distinguish among *immediate* (instantaneous), *gross*, and *net* effects. The direct effects again refer to the unaltered influence of marketing actions on a performance measure; indirect effects capture their impact on performance through competitive (or other) reactions. Among the direct effects, I distinguish between *immediate* effects and *gross* effects, or the sum of the direct effects over a specified time horizon. In addition, the *net* effects reflect the sum of the direct and indirect effects measured during the same time horizon and therefore account for competitive reactions, whereas gross effects do not. To estimate immediate, gross, and net effects, I use impulse response analyses (IRA). I illustrate the use of a VARX model by discussing a model specified and calibrated by Horvath et al. (2005). This model simultaneously considers advanced market response and advanced competitive reaction functions, and relies for calibration on pooled store data for each of three brands of tuna fish¹¹.

11 I closely follow Horvath et al. (2005). For a thorough discussion of VARX models see also Dekimpe et al. (2008).

3.6.1 RESPONSE FUNCTIONS

The (advanced) demand functions in this example are adaptations of AC Nielsen's SCAN*PRO model (see, e.g., Christen et al. (1997)) in which the variables of interest are the logarithms of the unit sales and price indexes (the ratio of actual to regular price) for brands at the store level. The SCAN*PRO model includes several own- and cross-brand promotional variables: price index, feature only, display only, and feature and display. Horvath et al. (2005) extend this model by including dynamic price promotion effects (delayed responses) and purchase reinforcement effects (through lagged sales). However, I do not include separate lagged non-price instruments to reduce concerns about the degrees of freedom. Horvath et al. allow for additional dynamic effects through lagged endogenous variables. Horvath et al. define two types of price promotion variables: own- and other-brand temporary discounts without support, and own- and other-brand temporary discounts with feature and/or display support. By definition, such promotion variables are minimally correlated.

All parameters are brand specific and all lagged variables have unique parameters. Horvath et al. (2005) specify the market response function as:

$$\begin{aligned} \ln S_{qi,t} = & \alpha_{qi} + \sum_{k=1}^2 \sum_{j=1}^n \sum_{t^*=0}^{P_{ijk}^{SP}} \beta_{PI_{ijk,t^*}} \ln PI_{qjk,t-t^*} + \sum_{j=1}^n \sum_{t^*=1}^{P_{ij}^{SP}} \varphi_{ij,t^*} \ln S_{qi,t-t^*} \\ & + \sum_{j=1}^n \beta_{Fij} F_{qj,t} + \sum_{j=1}^n \beta_{Dij} D_{qj,t} + \sum_{j=1}^n \beta_{FDij} FD_{qj,t} + \varepsilon_{qi,t}, \\ & q = 1, \dots, Q, i = 1, \dots, n, \text{ and } t = 1, \dots, T \end{aligned} \quad (21)$$

where $\ln S_{qi}$ is the natural logarithm of sales of brand i in store q in week t ; $\ln PI_{qik,t}$ is log price index (actual to regular price) of brand i in store q in week t ; ($k = 1$ denotes the feature/display-supported price cuts and $k = 2$ denotes price cuts that are not supported); $F_{qj,t}$ is a feature-only dummy variable for *non-price* promotions of brand j in store q at time t ; $D_{qj,t}$ is a display-only dummy variable for *non-price* promotions of brand j in store q at time t ; $FD_{qj,t}$ is the combined use of feature and display supports of *non-price* promotions of brand j in store q at time t ¹²; α_{qi} is a store-specific intercept for brand i and store q ; $\beta_{PI_{ijk,t^*}}$ = (pooled) elasticity of brand i 's sales with respect to brand j 's price index; φ_{ij,t^*} is the (pooled) substitution elasticity of brand i 's sales with respect to competitive (j) sales in week t ($i \neq j$); β_{Fij} , β_{Dij} , β_{FDij} are the effects of feature-only (F), display-only (D), and feature and display (FD); P_{ijk}^{SP} represents the number of lags for price index variable k of brand i included in the equation for brand j ; P_{ij}^{SP} is the number of lags of the sales variable of brand i included in the equation for brand j ; n is the number of brands in the product category; Q is the number of stores; and $\varepsilon_{qi,t}$ are disturbances. Horvath et al. (2005) test for the equality of slopes across stores and fail to reject this null hypothesis. Therefore, the specification of the demand

12 The variables F , D , and FD only deviate from zero only if a feature/display exists but there is no price discount.

model does not allow for slope heterogeneity. This specification captures purchase reinforcement ($\varphi_{ii,t}$), immediate sales response (β_{P_{ijk},t^*} for $t^* = 0$), and delayed response (β_{P_{ijk},t^*} for $t^* > 0$).

3.6.2 REACTION FUNCTIONS

In the preceding discussion, I define the competitive reactions as the reactions of brand managers to the marketing activities of other brands, but this reaction is not the only possible type of reaction, nor is it necessarily the most efficient one. For example, managers often track market share or sales, and a drop in either measure may prompt them to react with a marketing instrument. Similarly, they track other brands' performances and may interpret an increase as a competitive threat. Therefore, I incorporate these ideas as feedback effects in the reaction functions (compare also Kotler (1965)). These reaction functions also include price indexes as in (21). However, I may doubt whether competitors react to price indexes. Horvath et al. (2005) use these indexes instead of regular or promotional prices because VARX models require the same set of model variables. The reaction functions also account for inertia in decision-making and coordination between own-brand instruments (internal decisions):

$$\begin{aligned} \ln PI_{qil,t} = & \delta_{qil} + \sum_{t^*=1}^{P_{iil}^{PP}} \gamma_{il,t^*} \ln PI_{qil,t-t^*} + \sum_{t^*=1, k \neq \ell}^{P_{iik}^{PP}} \gamma_{ik,t^*} \ln PI_{qik,t-t^*} \\ & + \sum_{k=1}^2 \sum_{j=1, j \neq i}^n \sum_{t^*=1}^{P_{ijk}^{PP}} \gamma_{ijk,t^*} \ln PI_{qjk,t-t^*} \\ & + \sum_{j=1}^n \sum_{t^*=1}^{P_{ijl}^{PS}} \eta_{ij,t^*} \ln S_{qj,t-t^*} + \nu_{qil,t} \end{aligned} \quad (22)$$

where the variables are defined as in equation (21) ($\ell = 1, 2$). The super- and subindexes of P indicate that the number of included lags may vary per equation and per variable. Equation (22) thus captures internal decisions (inertia in decision making: γ_{il,t^*} , intrafirm effects: γ_{ik,t^*} , $k \neq \ell$), competitive reactions (γ_{ijk,t^*} , $j \neq i$), and own-brand (η_{ii,t^*}) and cross-brand (η_{ij,t^*} , $j \neq i$) feedback effects, which refer to reactions to the consequence of an action. If marketing managers who track their own-brand market share or sales perceive a decrease in either measure, they may react by changing their marketing activities. They may also track and react to other brands' performance (cross-feedback effects). Horvath et al. (2005) estimate a VARX model based on Equations (21) and (22) using two data sets covering two years of observations of weekly data. The data sets represent 24 (tuna fish) and 27 (shampoo) stores.

Before I continue my discussion of the possibilities of modeling competitive behavior, I believe a summary is appropriate. Thus far, I have described six different approaches. I summarize their characteristics in Table 2.

Table 2: Characteristics of methods to model competitive response for individual brands

Method	Characteristics
(1) Classical demand models	Simple, no interactions among actions, reactions and response.
(2) Classical LNB model	Interactions, aggregation of competitive brands, horizontal competition, no effects of retailers' decisions.
(3-5) Extended LNB models	Interactions, actions and reactions of/on individual brands, horizontal competition, accounting for effects of retailers' decisions, no simultaneous equation system (framework instead), no explanations of reactions.
(6) VARX models	Interactions, individual brands, horizontal competition, accounting for retailers' decisions, simultaneous equation system with emphasis on dynamic effects, some explanation of competitive moves.

The models (1)–(6) constitute a string of models that were developed by generations of model builders in an evolutionary way. This evolution covers a period of more than 30 year (1975–2005). The models we have discussed so far all assume that each manager treats the competitors' strategies as a given and computes his or her own best response. In the models that we will discuss next, managers achieve simultaneous solutions for, at least in principle, all relevant brands in the marketplace. Such simultaneous solutions call for game-theoretic approaches.

3.7 GAME-THEORETIC MODELS

The preceding discussions make it clear that in the market place, managers consider not only their perceptions of consumer responses, but also their expectations of competitor reactions to a potential marketing initiative. These complexities make the choice of an action in a competitive situation intractable, because the optimal choice for one brand depends on what other brands may do, which in turn depends on what the focal brand does, and so on (Moorthy (1985)).

Game theory offers a way to study these interdependencies¹³. The game-theoretic models of competitive responsiveness result from applying existing approaches to 'new' problems. Game-theoretic models are based on the assumption that competitors' strategies are

13 For more complete treatments of game theory in a marketing context, see Hanssens et al. (2001); Erickson (1991); Moorthy (1985; 1993). A managerial treatment of game theoretic principles appears in Brandenburger and Nalebuff (1996). For a general introduction to modern game theory, see Fudenberg and Tirole (1991); Mas-Collell et al. (1995).

given. In these models, one is interested in the specification of optimal marketing decisions for all (relevant) brands. The game-theoretic models originate from another branch of models, which is different from the models (1-6) discussed so far. In other words, they do not result from previous steps in the evolutionary process that I describe above.

Game theory separates into cooperative and non-cooperative categories. Cooperative game theory examines the behavior of colluding firms by maximizing a weighted average of all firms' profits. If two firms with profits π_1 and π_2 then:

$$\max_{x_{\ell j}} \pi = \lambda \pi_1 + (1 - \lambda) \pi_2 \quad (23)$$

where λ is the weight for firm 1; and $x_{\ell j}$ is the marketing instrument ℓ of firm j , $j = 1, 2$, $\ell = 1, \dots, L$. In empirical studies, the weight λ is determined by the data.

In the real world, competition takes place among a few competitors with interdependent interests such that each competitor's actions affect the others. This situation is characterized by strategic competition, which requires non-cooperative game theory. The Nash (1950) theory of equilibrium represents the central concept of noncooperative game theory and involves a set of strategies, one for each competitor, defined such that no competitor wants unilaterally to change its strategy. In a Nash equilibrium, each strategy is a competitor's best option, given the best strategies of its rivals, where the meaning of "best" depends on specified objectives. If the objective is profit, Nash equilibria are obtained for all ℓ and j :

$$\frac{\delta \pi_j}{\delta x_{\ell j}} = 0, j = 1, \dots, n, \ell = 1, \dots, L \quad (24)$$

where $\pi_j = f(x_{\ell j})$.

3.8 THE NEW EMPIRICAL INDUSTRIAL ORGANIZATION (NEIO)-BASED APPROACH: HORIZONTAL COMPETITION

The move from theoretical, static game-theoretic models to empirical, dynamic models has shifted attention from normative models to *descriptive game theory*, which implies using game-theoretic models to test whether marketplace data are consistent with model specifications. Empirical research in marketing strategy examines the impact of cost and competitive characteristics of a market on the profitability of a firm and generally follows the (market) structure-conduct (marketing mix, entry of new products, R&D expenditures) -performance(profitability)-paradigm (SCP paradigm) of empirical industrial organization (EIO) theory. Empirical studies use cross-sectional data across industries to find empirical regularities. Research that applies advanced game theory has also led to the insights that conduct and performance are not merely functions of structural market characteristics, such as concentration, growth, barriers to entry, and product differentiation, which are used in SCP studies. These insights provide the basis for NEIO studies. These studies focus on developing and estimating structural econo-

metric models of strategic, competitive behavior by firms, in which context “structural” means that the firm’s decisions are based on some kind of optimizing behavior, and “econometric models” reflect simultaneous equations of demand and supply of all relevant competitors.

Usually, an NEIO model contains the following ingredients: demand functions, cost functions, specifications for competitive interactions, and an objective function (usually a profit function). Furthermore, the consecutive steps required to specify and estimate empirical game theory models are:

1. Specify demand functions (including competitive marketing instruments).
2. Specify cost functions.
3. Specify objective functions (usually profit functions).
4. Specify the game.
5. Derive first-order conditions for optimal marketing instruments.
6. Add observed variables to identify the system.
7. Estimate the models.

Simultaneous equation models usually rely on a simultaneous equation instrumental variable approach for estimation, such as the three-stage least squares (3SLS), full information maximum likelihood (FIML), and generalized method of moments (GMM) approaches. Dubé et al. (2005) discuss various other computational and methodological issues, and Chintagunta et al. (2006) offer a review of structural modeling in marketing. Roy et al. (2006) compare the methods proposed in the NEIO studies.

As an example, I cite Gasmi et al. (1992), who investigate the behavior of Coca-Cola® and Pepsi®, using quarterly data covering 18 years from the United States about quantity sold, price and advertising. They estimate various model specifications to allow for the possible existence of both cooperative and noncooperative strategic behavior in this industry (“the game”). Their work specifies an objective function for each firm (profit function), as well as demand and cost functions. Using these specifications, they obtain a system of simultaneous equations based on assumptions about the firms’ behavior. Throughout their work, they also assume a one-to-one relation between firm j and brand j and therefore use those terms interchangeably. Gasmi et al. (1992) propose the following demand function for brand j :

$$q_j = \gamma_{j0} + \alpha_{jj}p_j + \alpha_{jr}p_r + \gamma_{jj}a_j^{1/2} + \gamma_{jr}a_r^{1/2}, j \neq r, j, r = 1, 2 \quad (25)$$

where q_j is the quantity demanded from brand j ; p_j is the price per unit for brand j , and a_j is the advertising expenditure for brand j .

I omit an error term and a subscript t for time periods from Equation (25) for convenience. To illustrate the use of this model, I assume the cost function is:

$$C_j(q_j) = c_j q_j, \quad (26)$$

where c_j is the constant variable cost per unit of brand j .

Therefore, I can write the profit function as:

$$\begin{aligned}\pi_j &= p_j q_j - C_j(q_j) - a_j \\ &= (p_j - c_j)(\gamma_{j0} + \alpha_{jj}p_j + \alpha_{jr}p_r + \gamma_{jr}a_j^{1/2} + \gamma_{jr}a_r^{1/2}) - a_j.\end{aligned}\quad (27)$$

In addition, Gasmi et al. (1992) consider six games:

1. Firms set prices and advertising expenditures simultaneously (naive static Nash behavior in price and advertising).
2. Firm $j = 1$ is the leader in both price and advertising, and firm $r = 2$ is the follower.
3. Firm $j = 1$ is the leader in price, but the two firms “behave Nash” in advertising.
4. Total collusion exists, which maximizes Equation (23), a weighted average of both firms’ profits.
5. Firms first collude on advertising, and later compete on prices.
6. Firms collude on price, knowing that they will compete later on advertising expenditures.

The first three games are based on noncooperating behavior, and the last three games consider tacit collusion.

Gasmi et al. (1992) include additional exogenous variables and specify functions for the demand intercepts (γ_{j0}) and marginal costs (c_j), which makes the system identifiable. These functions, together with the demand functions in Equation (25), can be estimated as a system of simultaneous equations. Thus, they derive a general model specification, which they use to test the six games. The empirical results suggest that for the period covered by the sample (1968-1986), there was tacit collusive behavior between Coca-Cola and Pepsi in their advertising in the market for cola drinks, though collusion on prices is not as well supported by the data. Thus, the results favor the specification for game 5.

The Gasmi et al. (1992) study deals with horizontal competition and collusion, but their model can also be extended to consider vertical competition/collusion between competitors/partners in the marketing system (Jeuland and Shugan (1983)). The structure of the demand Equation (25) also appears in other game-theoretic models, such as studies by Kadiyali (1996) and Putsis and Dhar (1999). For other demand equations, see Vidale and Wolfe (1957)¹⁴. Furthermore, in the past decade, aggregate logit models have become the prevalent demand functions¹⁵. This development also follows an evolutionary approach in which an earlier specification is improved over time. This development also holds for the next group of models, NEIO models that study vertical competition.

14 Also see Kimball (1957), and for examples, see Chintagunta and Vilcassim (1994); Erickson (1991); Naik et al. (2005).

15 See, for example, Chintagunta and Rao (1996); Sudhir (2001); Sudhir et al. (2005).

3.9 NEIO-BASED APPROACH: VERTICAL COMPETITION

The eight sets of models that I have discussed thus far deal primarily with horizontal competition. Therefore, these models cannot be applied if the focal company confronts vertical competition, which, in modern Western markets, almost always refers to competition between manufacturers and retailers. Historically, retailers have been local, fragmented, and technically primitive, which made it easy for some powerful multinational manufacturers to push them around. Within the span of two or three decades, this situation has become history. The largest retailers now enjoy global footprints, which has shifted power structures and increased vertical competition in the channels.

Many game-theoretic models deal with vertical competition, especially pass-through in channels, i.e., how retailers actually allocate the amount of money offered by manufacturers that is intended to stimulate consumer demand. Hence we are confronted with the application of an existing approach to a “new” problem. Models that consider vertical competition must simultaneously optimize the objective functions of at least two partners. Therefore, researchers apply game-theoretic approaches to determine joint, simultaneous solutions. As an example, I discuss the (general) structure of the pass-through model developed by Moorthy (2005), who considers two retailers (1 and 2), each with two brands, 1 and 2, such that brand 1 is common to both retailers and brand 2 is a private label. If D_{ij} , $i = 1, 2$, $j = 1, 2$, denotes brand j 's demand function at retailer i , the demand functions become the functions of all four retail prices: p_{11} , p_{21} , p_{12} , and p_{22} . Then, retailer i 's ($i = 1, 2$) category profit function is given by:

$$\pi_i(\tilde{p}) = (p_{i1} - w_1 - c_{i1} - c_i - c)D_{i1}(\tilde{p}) + (p_{i2} - c_{i2} - c_i - c)D_{i2}(\tilde{p}) \quad (28)$$

where \tilde{p} equals $(p_{11}, p_{21}, p_{12}, p_{22})$, w_1 is the wholesale price of the national brand, usually assumed to be common to both retailers; c_{i1} , c_{i2} represents the retailers i 's non-brand-specific marginal operating costs; and c represents the non-retailer-specific, non-brand-specific marginal operating costs.

Because brand 2 is a private label, the model provides no specific wholesale price for it. If the vector of marginal costs (w_1, c_{i1}, c_i, c) is taken as given and assuming that the demand functions are available, Moorthy is able to determine the optimal retail prices for both brands of both retailers. Solving the system of four first-order conditions leads to optimal price determinations, at least in principle¹⁶. Moorthy's (2005) is a non-empirical study.

3.10 TIME-VARYING COMPETITION

Normative models suggest that prices rise when demand and cost are higher, but in many markets, prices fall when demand or costs rise. This inconsistency occurs because norma-

¹⁶ The system of equations should have a negative-definite Hessian matrix. See for a similar model Villas-Boas and Zhao (2005).

tive models assume that competitive intensity is constant over time. Time-varying competition models do not assume about constant competitive intensity. These models explicitly consider the so-called *indirect effects* of demand and cost changes on competition, which complement the *direct effects* of demand and cost on prices¹⁷.

The idea of integrating competitive intensity in a game-theoretic model can be illustrated as follows. Consider a profit function π_{jt} of brand j at t ,

$$\max_{(p_{jt})} \pi_{jt} = M_t(p_{jt} - c_{jt})m_{jt} \quad (29)$$

where M_t is the potential size of the market at time t ; p_{jt} is the price per unit at time t ; c_{jt} is the cost per unit at time t ; and m_{jt} is the market share of brand j at t , where m_{jt} is a function of P_{jt} .

Solving the first-order conditions for profit maximization under the assumption of Nash-Bertrand equilibrium, I find

$$p_{jt} = c_{jt} - \frac{m_{jt}}{\frac{\delta m_{jt}}{\delta p_{jt}}}. \quad (30)$$

Therefore, the so-called Bertrand margin is

$$\text{margin}_{jt}^{\text{Bertr.}} = - \frac{m_{jt}}{\frac{\delta m_{jt}}{\delta p_{jt}}}. \quad (31)$$

In addition, I can capture the indirect effect of changes in competitive intensity on price by introducing a multiplier w_{jt} on the Bertrand margin. I can then specify the pricing equation as:

$$p_{jt} = c_{jt} + w_{jt} \text{margin}_{jt}^{\text{Bertr.}}. \quad (32)$$

The multiplier w_{jt} is a function of the predictor variables that affect competitive behavior. The interpretation of w_{jt} is as follows: When $w_{jt} > (<) 1$, firm j is pricing cooperatively (competitively) relative to the Bertrand equilibrium. At $w_{jt} = 0$, firm j prices at marginal cost. Sudhir et al. (2005) use quarterly dummy variables, which measure consumer confidence, costs of material and labor, and so forth, as predictor variables. By doing so, they explicitly model the indirect effects of demand and cost changes on competition.

3.11 DYNAMIC, EMPIRICAL GAME-THEORETIC MODELS

The last link in the evolutionary chain of building models of competitive response consists of dynamic, empirical game-theoretic models. The model developed by Ailawadi et al. (2005) comprises the following equations: demand equations for all brands in a product

¹⁷ See Sudhir et al. (2005).

category, the objective function of a retailer, and the objective function of a competitive brand. The context of the model that Ailawadi et al. (2005) consider is the retailers' and consumers' response to Procter & Gamble's (P&G) value pricing strategy, under which P&G made major cuts in promotions and provided a lower everyday price to its customers. Ailawadi et al. (2005) conduct their analysis for a local market and model the channel structure as a dynamic series of Manufacturer-Retailer Stackelberg games. In each period, P&G, the manufacturer of brand 1 is the leader and the retailer is the follower. I discuss the most important equations of the Ailawadi et al. model below:

Demand equations:

$$S_{its} = \alpha_{is} + \sum_{k=1}^K \beta_{iks} RP_{kts} + \sum_{k=1}^K \gamma_{iks} RD_{kts} + \delta_{1is} CD_{its} + \delta_{2is} (CD_{its})(RD_{its}) \quad (33)$$

$$CD_{its} = \lambda_i CD_{its-1} + (1 - \lambda_i) RD_{its-1} \quad (34)$$

where S_{its} is the unit sales of brand i in week t in store s ; $i, k = 1, 2, 3$ (1 is P&G, 2 is a competing national brand, and brand 3 is a private label); RP_{kts} , RD_{kts} is the regular retail price and regular deal amount per unit (discount) of brand k in week t in store s ; CD_{its} is cumulative dealing, i.e., the exponentially smoothed average of past retail deal amount for i , in t , in s ; and λ_i is an exponential smoothing parameter.

The retailer decides about the prices RP_{it} of the three brands and what retail deal amount to offer on the private label RD_{3ts} . She also decides how much of the national brands should be ordered (X_{1t} , X_{2t}). These order quantifiers are defined as X_{1t} and X_{2t} . Therefore the retailer's objective function is:

$$\max_{\substack{RP_{1t}, RP_{2t}, RP_{3t}, \\ RD_{3t}, X_{1t}, X_{2t}}} \sum_{t=1}^T \left\{ \sum_{i=1}^2 (RP_{it} - kD_{it}I_{it})S_{it} - (WP_{it} - D_{it})X_{it} - h_i INV_{it} \right. \quad (35) \\ \left. + (RP_{3t} - VC - RD_{3t})S_{3t} \right\}$$

where WP_{it} is the wholesale price; D is the trade deal amount offered by the manufacturer; k is the percentage of the trade-deal amount that the retailer offers to consumers in the weeks when she orders an trade deal; h is the retailer's unit inventory holding cost per period; VC is the variable cost of the private label to the retailer; I is an order indicator variable that is equal to one if an order is placed, and zero otherwise, and INV is inventor y defined as:

$$INV_{it} = INV_{i,t-1} + X_{i,t-1} - S_{i,t-1} \quad i = 1, 2. \quad (36)$$

Given that the retailer can order products prior to period t , the optimization of retail prices, the trade deal amount, and the order quantities are a dynamic programming problem.

Another important equation is the competing manufacturer's objective function, i.e., the objective function of brand 2. The brand 2 profit depends on whether the retailer buys from brand 2 or carries brand 2 forward from the last purchase order.

Brand 2's objective function is:

$$\max_{WP_{2t}, D_{2t}} \sum_{t=1}^T \{I_{2t}(WP_{2t} - VC - D_{2t})S_{2t} + (1 - I_{2t})(WP_{L_{2t}} - VC - D_{L_{2t}})S_{2t}\} \quad (37)$$

where $WP_{L_{2t}}$ and $D_{L_{2t}}$ are the wholesale price and the trade deal for brand 2 when it was last ordered by the retailer prior to period t .

Ailawadi et al. (2005) generate predictions of competitor and retailer responses and test their accuracy. To do so, they use weekly scanner data from stores in the Chicago market. The data represent the sales, deals, prices, etc., of nine product categories and over six years. Ailawadi et al. compare the predictive ability of their model with the reaction function approach (Leeflang and Wittink (1992; 1996)) and a dynamic model that assumes the retailer is nonstrategic. The dynamic, empirical game-theoretic model has better predictive ability than either benchmark model. Thus, such models provide the means to account for important changes in competitive strategy (see also Shugan (2005)) and are more consistent with strategic competitive reasoning than with the extrapolation of past reactions to the future.

It is clear that this model has evolved from several existing approaches and models, viz., NEIO models with horizontal (Set 8) and vertical competition (Set 9) which is time-varying (Set 10). The models also combine advanced demand functions (Set 4) with advanced competitive reaction functions (Set 3). Hence, the evolutionary steps are based on combinations of different research models. The models (7), (8), (9), and (11) constitute an evolutionary path that covers a time period of about 180 years. With the development of the empirical game-theoretic models in the past 15 years, these models have proved their value in the area of competitive responsiveness. I expect that the dynamic, empirical game-theoretic models can be improved in the near future through the application of Dynamic Linear Models (DLM)¹⁸.

4 FINDINGS

The study of competition and competitive response has a long tradition in microeconomic theory, starting with the work of Cournot (1838) and Bertrand (1883), and continuing with the development of multiple models of competitive responsiveness in the past 30 years. These studies on competitive responsiveness can be classified according to different (overlapping) criteria, such as¹⁹ area of application, type of competition, type of competitive strategies, and type of analyses. To expand on my summary of different types of anal-

18 See Van Heerde et al. (2004); Ataman et al. (2006); Ataman et al. (2007).

19 See also Horváth (2003), which is based on Leeflang (2001).

yses in Section 3, here I discuss several examples of studies that employ the first three criteria.

4.1 AREA OF APPLICATION

Most studies on competitive responsiveness refer to frequently purchased consumer goods (FPCG) and consider manufacturers' actions and reactions. The most prominent examples are studies by Nijs et al. (2001), and Steenkamp et al. (2005), who study 1,200 brands of 442 FPCG categories. Several studies analyze competition in durable goods markets. For example, Lambin et al. (1975) investigate competition among manufacturers of electronic razors in the West German market, Sudhir (2001) studies car markets, and Kadiyali (1996) and Sudhir et al. (2005) address the competitive responsiveness of two major players in the U.S. photographic film industry market.

In another arena, Jain et al. (1999) and Roberts et al. (2005) examine competition in the telephone industry by specifically considering service competition. Cleeren et al. (2006) study the competition of local services and model the entry of a new player on the video-rental market.

More recently, the numerous and rapid developments in information technology, especially the diffusion of information via the Internet, have enhanced the focus on competition among retailers, wholesalers, and manufacturers, who can now offer products through many and varied channels. An empirical study by Balasubramanian (1998) analyzes the entry of direct book marketers into a retail market. Bakos and Brynjolfsson (2000) examine the Internet's development as an infrastructure for distributing digital information goods. They conclude that through the large-scale bundling of information goods, the Internet has dramatically influenced competitive marketing and selling strategies. Other studies that consider the competition between the Internet and conventional channels include Lynch and Ariely (2000), who study the wine market; Clay et al. (2001) and Goolsbee and Chevalier (2002) for books; and Sørensen (2000), who examines the prescription drugs industry.

More recent articles also explore competitive responses in the context of retailing; several examples include Desai and Purohit (2004), Shankar and Bolton (2004), Wang (2004), and Padmanabhan and Png (2004).

Examples of models of competitive responsiveness in business-to-business (B2B) markets are more difficult to find. Lilien and Yoon (1990) investigate entry timing for new industrial products. Ramaswamy et al. (1994) consider competitive marketing behavior in industrial markets, and distinguish explicitly between retaliatory behavior (e.g., both firms cut prices or increase their marketing expenditures) and cooperative behavior (e.g., both competitors increase prices or decrease marketing expenditures). Ramaswamy et al. find that market concentration has the greatest impact on retaliatory behavior, although market growth and standardization also have a sizable influence, and that market growth has the greatest impact on cooperative behavior.

Chintagunta and Desiraju (2005) assess pricing and retailing behavior in the pharmaceutical industry for a specific class of prescription drugs across five countries. Therefore, their model accommodates market responses within markets and interfirm strategic interactions both within and across markets. These authors find considerable heterogeneity in preferences and market response across markets, which favor a regional strategic approach.

Other studies on competitive responses in an international marketing context deal with the speed of international market rollouts. These studies suggest that brands typically follow two types of strategies: a fast-rollout “sprinkler” strategy, in which the brand enters several countries at the same time; or a slow-rollout “waterfall” strategy, in which the brand enters several markets sequentially over time (Kalish et al. (1995)). Other studies in this field include those by Dekimpe et al. (2000), Tellis et al. (2003) and Gielens and Steenkamp (2004).

4.2 TYPE OF COMPETITION

The type of competition is characterized by the marketing mix instruments that dominate competition. For example, many competitive response models consider flexible price and non-price promotions and advertising²⁰. Unlike quality and distribution instruments, such marketing strategies usually display significant variation over time.

A topic that has received a great deal of attention in recent studies on competitive responsiveness is retail pass-through (Van Heerde and Neslin (2008)). The general problem of retail pass-through hinges on the question of how a retailer changes its prices when its costs change, either as a result of trade promotions or when a manufacturers change their regular wholesale prices. Retailers’ reactions to changes in costs appear in many studies, such as Neslin et al. (1995), Kim and Staelin (1999), Tyagi (1999), Kumar et al. (2001), Besanko et al. (2005), and Moorthy (2005). For example, Besanko et al. (2005) investigate the pass-through behavior of a major U.S. supermarket chain for 78 products across 11 categories. They find both positive and negative cross-brand pass-through effects, which indicates that retailers adjust the prices of competing products upward or downward in response to changes in the wholesale price of any particular product.

The oldest form of competition, price competition, continues to play a crucial role in many competitive response models, especially game-theoretic models. These models are used in studies by, e.g., Rao and Bass (1985), Dockner and Jørgensen (1988), Gasmi et al. (1992), Chintagunta and Rao (1996), Fruchter and Kalish (1997), Vilcassim et al. (1999), Hildebrandt and Klapper (2001), and Chintagunta and Desiraju (2005).

Moreover, modern research suggests a growing interest in calibrating competitive response models that deal with quality competition, as reflected in Lilien and Yoon (1990), Berndt et al. (1995), Dutta et al. (1995), Aoki and Prusa (1997), Lehmann-Grube (1997), Liu et

20 Leeflang and Wittink (1992; 1996; 2001); Dubé and Manchanda (2005); Horvath et al. (2005); Steenkamp et al. (2005).

al. (2004), and Chambers et al. (2006). In another developing field, Cohen and Klepper (1996), Sutton (1998), and Ofek and Sarvary (2003) examine research and development competition.

Pauwels and Srinivasan (2004) also demonstrate that store brand entry strengthens a retailer's bargaining position with regard to national brand manufacturers, though reactions to new entries have been studied in many other articles as well. A detailed description of the methods used in this context would require at least another article, so I mention only a few of the most important studies in this arena: Robinson (1988), Gatignon et al. (1989), Gatignon et al. (1997), Shankar ((1997); (1999)), Kalra et al. (1998), Narasimhan and Zang (2000), Waarts and Wierenga (2000), Deleersnijder et al. (2001), Debruyne and Reibstein (2005), Roberts et al. (2005), and Kornelis et al. (2008).

4.3 TYPE OF COMPETITIVE STRATEGIES

Most models that consider competitive responsiveness assume that competitive reactions are based on past observations, but models that rely on historical data, no matter how successful in the short run, generally cannot predict the impact of any future changes in competitive strategy²¹. Implementing entirely new (i.e., dynamic) strategies inevitably changes past behavior, and common marketing activities, such as new product development, repositioning, altering ancillary services, or major pricing-policy changes (Ailawadi et al. (2005)), alter the nature of competition among incumbents, thereby invalidating any relationships based on past observations. In turn, models must account for dynamic strategies, perhaps according to the principle of strategic foresight, a notion that requires managers to look forward and anticipate competing brands' likely future decisions. Managers may then reason backward to deduce their own optimal decisions in response to the best decisions to be made by all other brands (Naik et al. (2005)). Day and Reibstein (1997) and Montgomery et al. (2005) both confirm the need to develop strategic models; specifically, Day and Reibstein (1997) identify two strategic errors, the failure to anticipate competitors' moves (likely actions) and the failure to recognize potential interactions over time (reactions).

More recent models, such as those proposed by Rao et al. (1995), Chintagunta and Rao (1996), Vilcassim et al. (1999), Ailawadi et al. (2005), Dubé and Manchanda (2005) and Sudhir et al. (2005), also account for dynamic strategic decision making.

Another aspect that determines the type of competitive strategies is whether the focus is competition between firms/brands that is retaliatory behavior, or collusion, collusive/cooperative behavior. Gasmi et al. (1992) provide an empirical method for studying various forms of implicit and explicit collusive behavior in terms of price and advertising.

21 I closely follow Shugan (2005).

4.4 OUTCOMES

The models of competitive response that I introduce have generated outcomes of great value for policy decisions in actual practice.

4.4.1 UNDER- AND OVER-REACTIONS

Leeflang and Wittink (1996) find that marketing managers of Dutch detergent brands tend to over-react, even though no reaction represents the dominant competitive response mode. In a replication study, Brodie et al. (1996) confirm Leeflang and Wittink's finding with New Zealand data.

Steenkamp et al. (2005) study simple and multiple reactions to both price promotions and advertising, including both short- and long-term effects. They also examine the moderating impact of brand- and category-related characteristics on competitive reaction elasticities. In contrast to Leeflang and Wittink (1992; 1996), Steenkamp et al. (2005) distinguish two types of reactions: accommodations, i.e., reductions in marketing support after a competitive attack; and retaliations. On the basis of this differentiation they find that the most common form of competitive reaction is passive (no reaction) when reactions occur, they are more often in response to price promotions than to advertising; retaliation with a price promotion against price promotion attacks is more common than any other action reaction combination; simple competitive reactions are generally retaliatory, but multiple reactions can be either retaliatory or accommodating; and all forms of competitive reactions are generally restricted to short-term changes in brands' marketing spending, which do not prompt permanent changes in spending behavior.

Because the most common form of competitive reaction is *no reaction* to an attack (cells $C + D + G + H$ in Table 1), I question whether this decision is managerially sound, in the sense that sales protection appears unnecessary.

4.4.2 EXPLAINING COMPETITIVE REACTIONS

Dolan (1981) studies several industries and identifies four specific variables that determine the nature of competition: high fixed costs, which promote competitive reactions (to gain market share); low storage costs, which reduce competitive reactions; growing primary demand, which reduces competitive reactions; and large firms that avoid price competition.

Clark and Montgomery (1998) also propose and test a framework built around credibility and deterrence. Empirical results show that a credible reputation deters an attack if the potential attacker considers the target firm a minor competitor, but a major competitor is very likely to be attacked, independent of the target's credibility; the more successful a firm is, the more likely it is perceived as a credible defender; and that consistently high

levels of marketing activity relative to competitors help a firm gain a reputation as a credible defender.

These results are intriguing. It seems reasonable, for example, that managers would go after major competitors because large firms have more demand share to lose.

Chen et al. (1992) use a formal empirical approach to identify the characteristics of actions that lead to competitive reactions and test the hypothesized relationships with a sample of competitive moves among U.S. airlines. On the basis of their findings, they propose the following characteristics to explain competitive reactions.

- *The competitive impact*, which they define as the pervasiveness of an action's effect on competitors, measured by the *number of competitors* actually affected by an action (i.e., the number of airlines that served in at least one of the airports affected by the action of the initiator).
- *The attack intensity*, or the extent to which an action affects each competitor's key markets, measured as the *proportion of passengers* served by the airline who potentially are affected by the action.
- *The implementation requirement*, which refers to the degree of effort a firm requires to execute an action and reflects the amount of time between the announcement of an action and the date the action occurs (delay).
- *Type of action*, in terms of its strategic versus tactical nature of an action, such that a strategic action includes a significant investment in fixed assets and/or people and structures, whereas tactical actions do not involve such commitments.

They further operationalize the competitive reaction variables by citing the number of responses, the total number of competitors who reacted to an action (the number of counteractions), and the response lag, the length of time a competitor took to react to an initiator's action.

Chen et al. (1992) find that the number of competitive reactions relates positively to the competitive impact and attack intensity. Actions with greater implementation requirements and strategic (rather than tactical) actions provoke fewer counteractions, and that strategic actions and actions that require a substantial amount of time generate slower reactions.

Leeflang and Wittink (2001) use a more formal approach to explain competitive reaction effects. If brand $j(u_{\ell j})$ uses only one marketing instrument (ℓ) in reaction to a change in a marketing instrument h for brand $i(u_{hi})$, then to preserve market share, the reaction elasticity (RE) must equal:

$$RE = \rho_{u_{\ell j}, u_{hi}} = \frac{\eta_{m_j, u_{hi}}}{\eta_{m_j, u_{\ell j}}} \quad (38)$$

where $\eta_{m_j, u_{hi}}$ is the cross-elasticity for brand j with respect to i 's instruments, and $\eta_{m_j, u_{\ell j}}$ is the own elasticity for brand j with respect to j 's instrument ℓ . It follows from Equa-

tion (38) that the reaction elasticity (*RE*) relates positively to the (absolute) cross-brand market share elasticity and negatively to the own-brand market share elasticity. In their empirical analysis, Leeflang and Wittink (2001) also find support for the idea that competitive reaction elasticities are a positive function of cross-brand market share elasticities, and a negative function of own-brand market share elasticities.

In their large-scale empirical study of short-run and long-run reactions to promotions and advertising shocks, Steenkamp et al. (2005) uncover several factors that affect the intensity of competitive reactions. For simple reactions with price promotions and advertising, the reactions are stronger when the attacker is more powerful, the relative power structure in the dyad favors the defenders, the category is less concentrated, and the interpurchase time is higher. Price promotion reactivity is stronger in categories that involve more impulse buying. Finally, advertising reactivity is lower in growing categories, for storable products, and in categories with lower advertising intensity.

In Section 3 I discussed the application of a VARX model to determine the simultaneous effects of actions and reactions on sales over time. In a similar vein, to estimate gross and net sales, Horv  th et al. (2005) add forecasted sales effects over the dust-settling period and attempt to determine the impact on the sales effect of a firm's own competitive reactions; reactions to the consequences of own actions or competitive actions, i.e., own-feedback effects and cross-feedback effects, respectively; and internal decisions. (See also Equation (22)). The internal decisions represent intrafirm effects (relations between different variables of the same brand) and inertia (lagged endogenous variables). The Horv  th et al. research indicates that in terms of sales, cross-brand feedback effects are more relevant than are competitive reaction effects. This finding suggests that managers are more sensitive to competitors' sales than they are to competitors' actions. Thus, models must accommodate not only competitive reaction effects, but also cross-brand sales feedback effects. The same holds true for internal decisions: inertia and intrafirm decisions represent crucial determinants for specifying sales promotion decisions. These findings are in line with several recent studies that report that an aggressive competitive reaction does not constitute an important factor in market behavior (e.g., Pauwels (2004); Steenkamp et al. (2005)).

5 TAKING STOCK: IMPLEMENTATION

In this final section I distinguish among the models designed to support operational decisions and models that can be used to support strategic decisions. Models 1-6 can, at least in principle, predict short-term (operational) reactions. By substituting appropriate values of the marketing instruments into equations such as Equation (19), marketers may determine competitive reactions. Because these reactions lead to new reactions, the system of equations represented by Equation (21) and (22) may be more appropriate for determining the effects on both competitive reactions and sales on the long (or longer) term. Such effects can be determined only with appropriate assumptions about the expected values of the competitive marketing instruments. I recommend simulations that can deter-

mine the sensitivity of competitive reactions to different assumptions about competitive actions.

However, demand functions such as those summarized in Equations (1), (10), and (20) are the most valuable for attempts to determine whether to react to competitive actions. In general, only a limited number of competitors, who possess a limited number of marketing instruments, can actually affect own sales. Therefore, any estimation of demand models that includes competitive marketing instruments provides a basis for normative decision making. Demand equations also offer the basis to decide whether to react and thus may reduce over- and under-reactions.

Normative decision-making in marketing that accounts for competitive actions and reactions also may benefit from the findings and generalizations discussed in the preceding section, such that competitive reactions are stronger when the cross-brand elasticities are higher, and competitive reactions are weaker when the own-brand elasticities are higher.

Game-theoretic models assist normative decision making by determining the conditions for equilibriums between brands in the same product category (horizontal competition) and among agents (retailers, wholesalers, and manufacturers) in the same channel (vertical competition). Game-theoretic models based on empirical demand and reaction functions are useful in this type of scenario.

However, there is still the question of whether competitive response models are adequate tools to predict strategic changes. Ailawadi et al. (2005) demonstrate that game-theoretic models that consider vertical and horizontal competition and that are based on empirical demand equations are superior to reaction-based models (e.g., models 2-6) for predicting actual competitor and retailer responses to a major policy change. Thus, although it is based on a simplified reality, Ailawadi et al.'s model is quite complicated. Furthermore, optimal decisions based on normative models can be obtained analytically only when the number of horizontal and vertical competitors is limited. When the number increases, it is difficult to obtain substantive analytical solutions. Therefore, I suggest using simulations of these more complicated demand and supply systems, which may provide a means to derive the optimal solutions. Hence I conclude that more sophistication does not always mean an increase in the probability of model implementation.

In turn, the remaining challenges for this research area require that there be more adequate methods and approaches for predicting strategic response (Montgomery et al. (2005)); tailored models to fit unique situations²²; the development of models that are implemented in practice, as well as the development of models that supply knowledge about how competitive responses are generated.

22 An example of the latter models is a prelaunch diffusion model for evaluating market defense strategies in the telecom sector developed by Roberts et al. (2005).

Following Shugan ((2004); (2005)), I believe that endogenizing competitive responses, i.e., adding more variables to the models, is beneficial. In this respect researchers might explore the ideas articulated by Soberman and Gatignon (2005), which suggest a link between competitive dynamics and market evolution. The potential link between these two areas offers many opportunities to enrich the theory of model evolution, as well as the theory and practice surrounding competitive responsiveness. New models that have the desired characteristics are at the end of the evolutionary model chain. However, I believe that, given the discussion above, there is room for different models for different niches.

In this respect I wish to emphasize developments that are highly promising. The first is the development and application of Dynamic Linear Models. These models offer many opportunities to account for dynamics in competitive response. Recent developments in new empirical industrial organization models, including structural modeling, also offer new avenues for future developments.

The models I present in this survey have been applied in a wide array of areas, but in other areas they have barely been used at all, nor will they be. This inapplicability is because the data they require are not available in areas such as business-to-business markets or services (e.g., banking, insurance, industrial), which have intensive competitive battles that the traditional scanner data-based models that I present here do not model. Furthermore, most models consider price-, non-price, and advertising competition, but competition through and between retailers has not been fully exploited.

In this survey I also illustrate how an evolutionary model-building process may proceed in the science of marketing. The idea of evolutionary model building can be applied to make explicit relations between different kinds of models and to specify future directions of research. Models evolve for many reasons, including the availability of new specifications, new estimation methods, access to better data, the identification of opportunities to improve the specification, and new ideas to combine different research streams. The area of competitive response models still offers many opportunities for development along these lines.

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